

**TRANSFORMER FAILURE PREDICTION IN DISTRIBUTION POWER SYSTEM
NETWORK USING ARTIFICIAL NEURAL NETWORK**

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NETWORK USING ARTIFICIAL NEURAL NETWORK**

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**A DISSERTATION SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES
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ELECTRONICS ENGINEERING, COLLEGE OF ENGINEERING, COVENANT
UNIVERSITY.**

SEPTEMBER, 2021

ACCEPTANCE

This is to attest that this dissertation is accepted in partial fulfillment of the requirements for the award of Masters of Engineering degree (M.Eng) in Electrical and Electronics Engineering, Department of Electrical and Information Engineering, College of Engineering, Covenant University Ota, Nigeria.

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DECLARATION

I, **NGEREM, ELVIS ONYEDIKACHI (18PCK02056)**, declares that this research was carried out by me under the supervision of Prof. Anthony U. Adoghe of the Department of Electrical and Electronics Engineering, College of Engineering, Covenant University, Ota, Nigeria. I attest that the dissertation has not been presented either wholly or partially for the award of any degree elsewhere. All sources of data and scholarly information used in this dissertation are duly acknowledged.

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Signature and Date

CERTIFICATION

We certify that this dissertation titled "**TRANSFORMER FAILURE PREDICTION IN DISTRIBUTION POWER SYSTEM NETWORK USING ARTIFICIAL NEURAL NETWORK**" is an original research work carried out by **NGEREM, ELVIS ONYEDIKACHI (18PCK02056)** in the Department of Electrical and Information Engineering, College of Engineering, Covenant University, Ota, Ogun State, Nigeria, under the supervision of Prof. Anthony U. Adoghe. We have examined and found this work acceptable as part of the requirements for the award of Master of Electrical and Electronics Engineering.

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DEDICATION

This research is dedicated first and foremost to God Almighty, the source of all wisdom, knowledge, and understanding, for His grace and favor over the course of this research. Then to my family for their endless love and support.

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LIST OF ABBREVIATIONS

Σ - Summation

ϕ - Activation Function

μ - Feature average

σ – Standard deviation

AI – Artificial Intelligence

ANN - Artificial Neural Network

ML – Machine Learning

KNN – K-Nearest Neighbors

DGA - Dissolved Gas Analysis

H₂ – Hydrogen

CH₄ - Methane

C₂H₂ – Acetylene

C₂H₄ – Ethylene

C₂H₆ - Ethane

CO - Carbon monoxide

N₂ - Nitrogen

O₂ - Oxygen

CO₂ - Carbon dioxide

OLTC – On Load Tap Changer

PD – Partial Discharge

HPLC – High-Performance Liquid Chromatography

TCN - Transmission Company of Nigeria

AC - Alternating Current

MLP - Multilayer Perceptron

SMOTE – Synthetic Minority Oversampling Technique

SVC- Support Vector Classifier

ReLU – Rectified Linear Unit

TP – True Positive

TN – True Negative

FP – False Positive

FN – False Negative

AUC – Area Under the Curve

ROC – Receiver Operator Characteristic

TNR – True Negative Rate

TPR - True Positive Rate

FPR – False Positive Rate

RMSE - Root Mean Square Error

IDE – Integrated Development Environments

MATLAB – Matrix Laboratory

ABSTRACT

Distribution Transformers (DTs) are critical components of the power distribution network, and their reliability is heavily reliant on them, necessitating the need for a thorough and precise maintenance process focused on the prediction of impending transformer faults. Distribution transformers are subjected to both internal and external faults as a result of the electrical, mechanical and thermal stresses they are subjected to during their operation, resulting in irregularities in some of their cooling and insulating materials, such as oil and cellulose insulation degradation. These lead to overheating, partial discharge, or corona, causing a degradation of the oil insulation and the introduction of dissolved gasses such as hydrogens (H_2), carbon monoxide (CO), carbon dioxide (CO_2), methane (CH_4), acetylene (C_2H_2), ethane (C_2H_6), and ethylene (C_2H_4). In this project, an Artificial Neural Network (ANN) model in python programming for the diagnosis of incipient faults of distribution transformers, using the DGA (Dissolved Gas Analysis) concentrations, was developed. Also, four machine learning models are developed for fault prediction from dissolved gas analysis data in distribution transformers using interpretation results from Roger's ratio, IEC basic ratio, and Dornenburg Ratio on the basis of the IEEE C57.104 standard. The models developed are K-nearest neighbors, linear support vector classifier, logistic regression, and multilayer perceptron. These models were trained, tested, and evaluated to determine the best performing model. The identified best-performing model was implemented on a web based interacting application interface. A transformer fault prediction algorithm trained with back-propagation resulted in an improved accuracy of 97.93%. This will aid maintenance engineers for a faster and accurate diagnostic decision on faulty distribution transformers as it plays a significant role in power supply to large energy customers.

Keywords: Artificial Neural Network, Dissolved Gas Analysis, Distribution transformers, transformer failure, fault prediction.